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Reduced Ordering Based Approach to Impulsive Noise Suppression in Color Images

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***Abstract*—In this paper a novel filtering design intended for the impulsive noise removal in color images is presented. The described scheme utilizes the rank weighted cumulated distances between the pixels belonging to the local filtering window. The impulse detection scheme is based on the difference between the aggregated weighted distances assigned to the central pixel of the window and the minimum value, which corresponds to the rank weighted vector median. If the difference exceeds an adaptively determined threshold value, then the processed pixel is replaced by the mean of the neighboring pixels, which were found to be not corrupted, otherwise it is retained. The important feature of the described filtering framework is its ability to effectively suppress impulsive noise, while preserving fine image details. The comparison with the state-of-the-art denoising schemes revealed that the proposed filter yields better restoration results in terms of objective restoration quality measures.**

***Index Terms*—color image processing, noise reduction, image enhancement**

I. Introduction

Quite often the quality of color images is degraded by various types of noise, whose removal is required to enable the success of further steps in the image processing pipeline. Noise, arising from a variety of sources, is inherent to electronic image sensors and therefore the noisy signal has to be processed by a suitable filtering algorithm that reduces the noise component, while preserving original image details [1-3].

In this work we focus on a special kind of distortion, which is introduced by impulsive noise caused by malfunctioning sensors, faulty memory locations in hardware, aging of the storage material or transmission errors due to natural or man-made processes [4-6].

The color image will be treated as a two-dimensional matrix consisting of pixels $x_u = (x_{u1}, x_{u2}, \ldots, x_{uv})$, where the index $u = 1,\ldots,N$ indicates the pixel position on the image domain and v denotes the number of channels. In the case of standard color images $v=3$. The vector components x_{uk}, for $k = 1,2,3$ represent the RGB color channels values.

Generally, filtering operators work on the assumption that the local image features can be extracted from a small image region centered at pixel x_u, called a *sliding filtering window* and denoted as *w*. Thus, the output of the filtering operation will depend only on the *n* samples contained within the filtering window centered at x_u, which will be also denoted for convenience as , so that $W = \{x_1, x_2, \ldots, x_n\}$.

The majority of the nonlinear filters used for impulsive noise removal in color images is based on the order statistics [7]. These filters perform the *vector ordering* of the set of pixels from the filtering window to determine the filtering output. The widely used *reduced vector ordering* is based on assigning a dissimilarity measure to each color pixel from the filtering window [1,8,9]. The aggregated dissimilarity measure assigned to pixel x_i is defined as

$$R_i = \sum_{j=1}^{n} \rho\left(x_i, x_j\right), \quad x_i, x_j \in W, \tag{1}$$

where $\rho(\cdot)$ denotes the distance between pixels in a given color space. The values of R_i, $(i = 1,\ldots,n)$ are then sorted and the vectors $x_1, x_2, \ldots, x_n$ are correspondingly ordered

$$R_{(1)} \leq \cdots \leq R_{(n)} \;\Rightarrow\; x_{(1)} \prec \cdots \prec x_{(n)}, \tag{2}$$

where $\prec$ denotes the order relation between vectors and $R_{(k)}$ denotes the *k*-th smallest value of *R*.

Many denoising techniques define the vector $x_{(1)}$ in (2) as their output, since vectors that diverge significantly from the samples of *w* appear in the higher indexed locations in their ordered sequence.

One of the most widely used noise reduction techniques is the Vector Median Filter (VMF), whose output is the vector $x_{(1)}$ from *W*, for which the sum of distances to all other vectors is minimized

$$x_{(1)} = \arg\min_{x \in W} \textstyle\sum_{j=1}^{n} \|x - x_j\|, \tag{3}$$

where $\|\cdot\|$ denotes Euclidean norm. The VMF is the most popular operator intended for smoothing out the impulses injected into the color image by the noise process. This filter is very efficient at reducing the impulses, preserves sharp edges and linear trends. However, the drawback of the VMF and other filters based on vector ordering lies in introducing excessive smoothing, which results in an extensive blurring of the output images. Thus, the filters based on vector ordering do not preserve fine image structures, which are treated as noise and therefore generally show a tendency to the blurring of image details and generation of color artifacts.

In order to alleviate the problem of image smoothing various *switching filters*, that replace only the corrupted pixels have been proposed [10-13]. The efficiency of a switching filter depends both on the quality of the impulse detection scheme and on the applied restoration framework, which replaces the detected impulses with estimates derived from the samples belonging to a local processing window.

In this paper a novel switching filter is proposed. The main advantage of the proposed approach is its ability to suppress the noise component, while preserving fine image

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details. The structure of the filter is based on the reduced ordering statistics and is characterized by a low computational complexity, which enables the adoption of the new technique in real-time applications.

II. Rank Weighted Filtering Design

The reduced ordering schemes are based on the sum of the dissimilarity measures between a given pixel and the samples from the local filtering window *w*. In this way, the output of the vector median filter is the pixel whose average distance to other pixels is minimized.

The distances $\rho_{ij} = \rho(x_i, x_j)$ between the pixel x_i and all other pixels *w* belonging to can be arranged into a sequence

$$\rho_{i1}, \rho_{i2}, \ldots, \rho_{in} \rightarrow \rho_{i(1)}, \rho_{i(2)}, \ldots, \rho_{i(n)}, \quad (4)$$

and the ranks of the ordered distances can be used for the evaluation of the aggregated distances in (1).

If stands for the rank of a given distance, then $\rho_{i(r)}$ will denote the corresponding distance value and instead of the aggregated distances in (1) a weighted sum of distances, utilizing the distance ranks, can be composed

$$D_i = \sum_{r=1}^{n} f(r) \cdot d_{i(r)}, \quad (5)$$

where *f(r)* is a decreasing weighting function of the distance rank *r*. Then, the rank weighted sums of distances D_i can be sorted and a new sequence of vectors is obtained

$$D_{(1)}, D_{(2)}, \ldots, D_{(n)} \rightarrow \tilde{x}_{(1)}, \tilde{x}_{(2)}, \ldots, \tilde{x}_{(n)}, \quad (6)$$

where the vector $\tilde{x}_{(1)}$ is the output of the Rank Weighted Vector Median Filter (RWVMF). Applying a step-like function

$$f(r) = \begin{cases} 1, & \text{for } r \le \alpha,\ \alpha \le n, \\ 0, & \text{otherwise}, \end{cases} \quad (7)$$

the Sharpening Vector Median Filter (SVMF) presented in [14] is obtained.

Extensive experiments revealed that satisfactory denoising results are achieved using monotonously decreasing function *f(r) = 1/r* [15-17]. The weighting function decreases the influence of large distances introduced by the outliers injected by the noise process, which enables to efficiently remove the impulsive noise while enhancing the image edges.

III. Adaptive Switching Filter

In order to decide whether a pixel of a color image is corrupted by impulsive noise, the difference between the cumulated weighted distance D_1 assigned to the central pixel of the filtering window and the value of $D_{(1)}$ corresponding to the rank weighted vector median filter output can be used [15-17] and the strength of the impulsive contamination can be estimated as the difference between D_1 and $D_{(1)}$.

Figures 1 and 2 show examples of the detected noise using parts of the color test images *Parrots* and *Goldhill* corrupted by impulsive noise, whose intensity *p* denotes the percentage of corrupted pixels. The visual comparison of the real and detected noise confirm the good efficiency of the proposed method. It can be observed that the map of the detected noise correlates very well with the real contamination measured as the Euclidean distance between the original and corrupted pixels in the RGB color space normalized to the range < *0,255*>. Figure 3 exhibits the correlation between the real and the detected impulsiveness of the image pixels using the test images *Goldhill* and *Parrots*. The results reveal a high correlation between the real and detected noise.

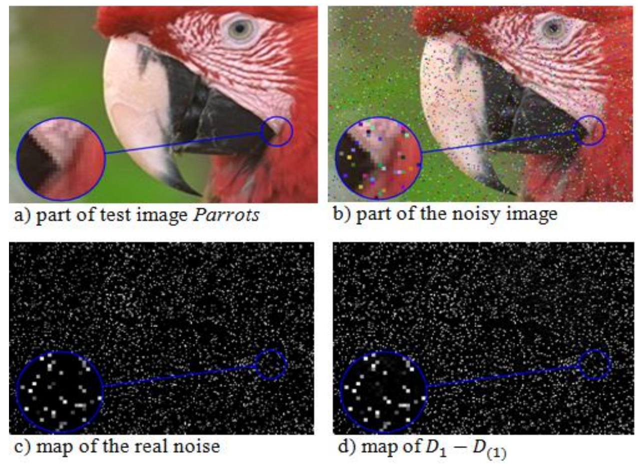

Figure 1. Illustration of the noise detection efficiency using the *Parrots* image corrupted by impulsive noise with *p*=0.1 intensity.

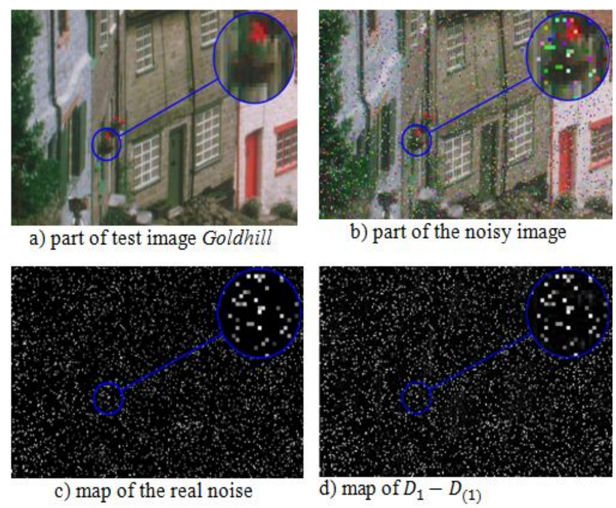

Figure 2. Illustration of the noise detection efficiency using the *Goldhill* image corrupted by noise with *p*=0.1 intensity.

Figure 4 shows the histograms of the corresponding values of D_1, $D_{(1)}$ and the measure of impulsiveness $D_1 - D_{(1)}$ for different levels of noise intensity using the *Parrots* test image. As can be seen, with increasing level of noise intensity, the histograms are shifted towards higher values, which is confirmed by the mean value of $D_1 - D_{(1)}$ marked with a red line on the plots.

The structure of the proposed switching filter is quite simple. If the difference $D_1 - D_{(1)}$, which measures the pixel corruption, exceeds a given threshold value , then a pixel is declared as corrupted by a noise process, otherwise it is treated as not disturbed

$$y_1 = \begin{cases} \hat{x}, & \text{if } D_1 - D_{(1)} > T, \\ x_1, & \text{otherwise}, \end{cases} \quad (8)$$

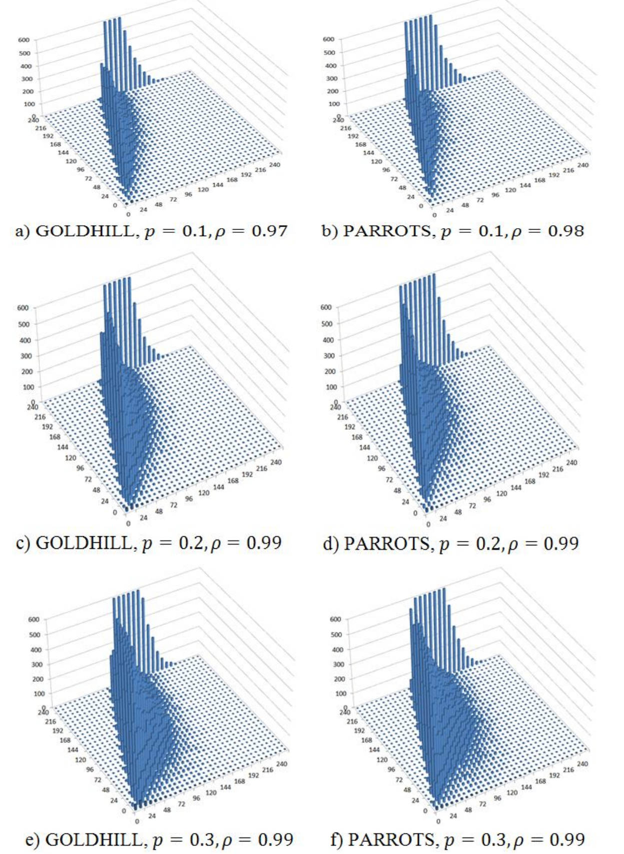

Figure 3. Illustration of the correlation between the real noise and the output of the proposed noise detector for different levels of noise intensity. The correlation coefficient p is provided for each plot.

where y_1 is the switching filter output, x_1 is the central pixel of the filtering window and $\hat{x}$ is the Arithmetic Mean Filter output computed using only the pixels found by the detector to be not corrupted by the noise process. If all neighbors of the central pixel x_1 of the filtering window are declared as corrupted, then the VMF applied to all pixels from w is taken as the filter output.

Of course, the efficiency of the switching scheme is dependent mainly on the value of the thresholding parameter. If the threshold T is too low, the filter will be replacing uncorrupted pixels and much of the image details will be lost. On the other hand, if the value of T is too high, many corrupted pixels will pass the filter without being processed.

As could be expected, the optimal setting of T depends on the contamination intensity. As can be observed in Fig. 6, which shows the dependence between the optimal threshold τ value and the noise contamination level p evaluated using a set of test images shown in Fig. 5, the threshold yielding the best PSNR value is decreasing with increasing noise contamination level and does not depend significantly on the image structure.

Therefore, the thresholding parameter T needs to be adjusted to the noise intensity level. The experiments performed using the set of images shown in Fig. 5, indicate an approximately linear dependence between the contamination ratio p and the mean value of the impulsiveness measure $D_1 - D_{(1)}$ computed for all image pixels and denoted as μ, (see also Fig. 4). The dependence between the average impulsiveness measur μ and noise intensity level p is shown in Fig. 7.

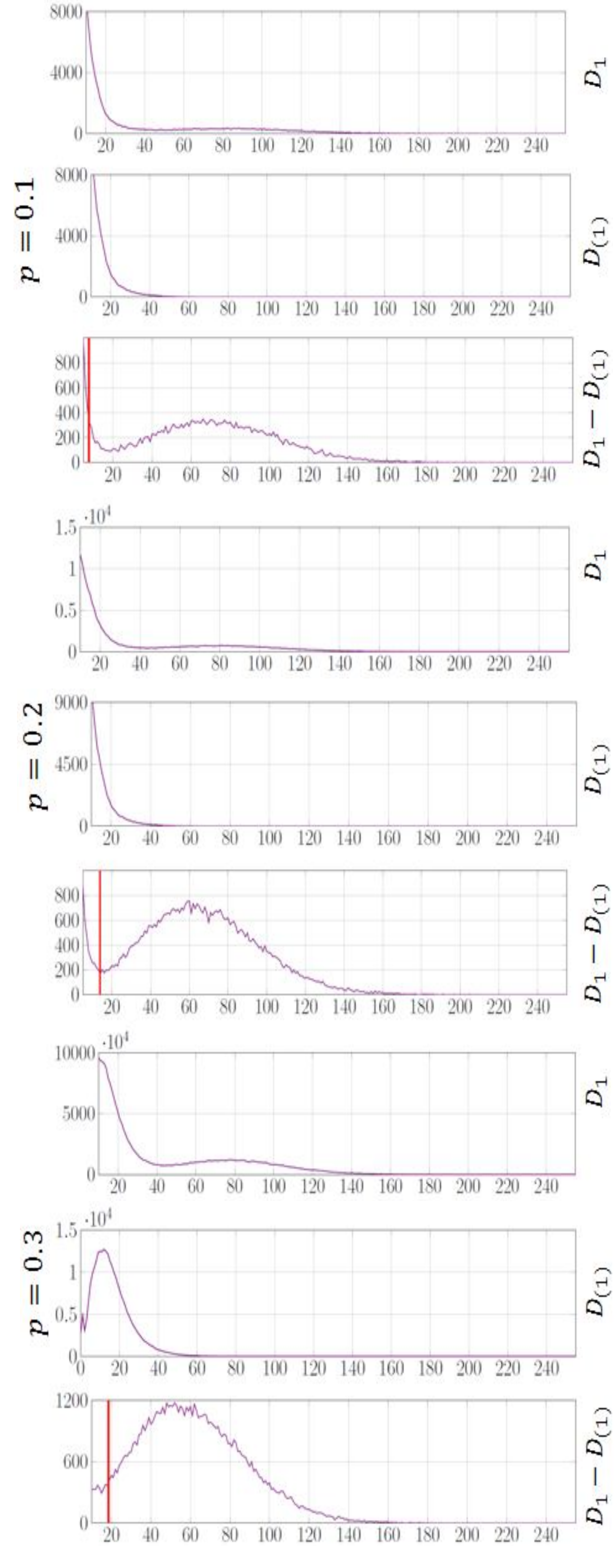

Figure 4. Histograms of the values of D_1, $D_{(1)}$ and D_1 - $D_{(1)}$ created using the PARROTS image contaminated by the impulsive noise with different intensities. The red line marks the mean value of a histogram.

Figure 5. Color test images used for the construction of an adaptive filter.

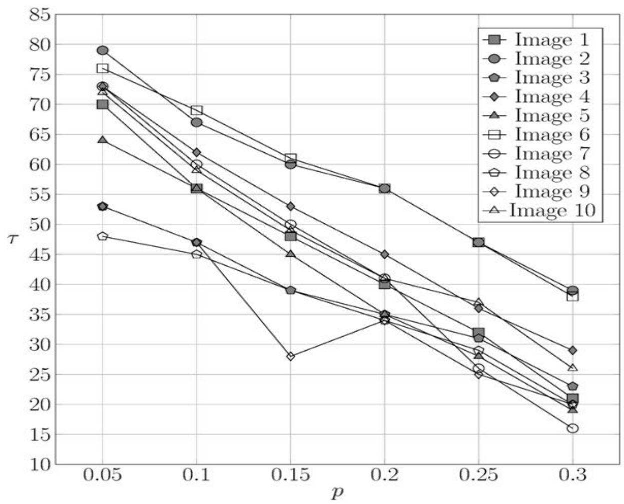

Figure 6. Dependence of the optimal threshold τ on the contamination level p for the images shown in Fig. 5 corrupted by impulsive noise.

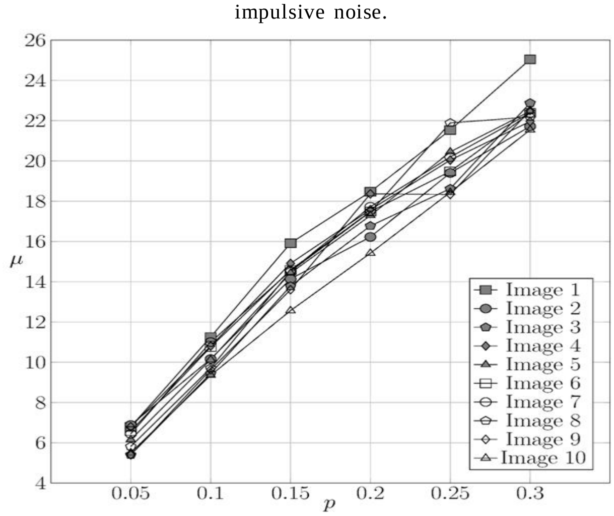

Figure 7. Dependence of the measure of impulsiveness μ on the contamination level for color images depicted in Fig. 5.

Combining these plots, we obtain the scatter plot depicted in Fig. 8, which reveals a roughly linear dependence between the optimal value of the adaptive threshold τ and the value of μ

$$\tau = -2.87 \cdot \mu + 66.5, \tag{9}$$

which can be used for the adaptive setting of the appropriate threshold value enabling high efficiency of the proposed filter for low and moderate noise contamination levels.

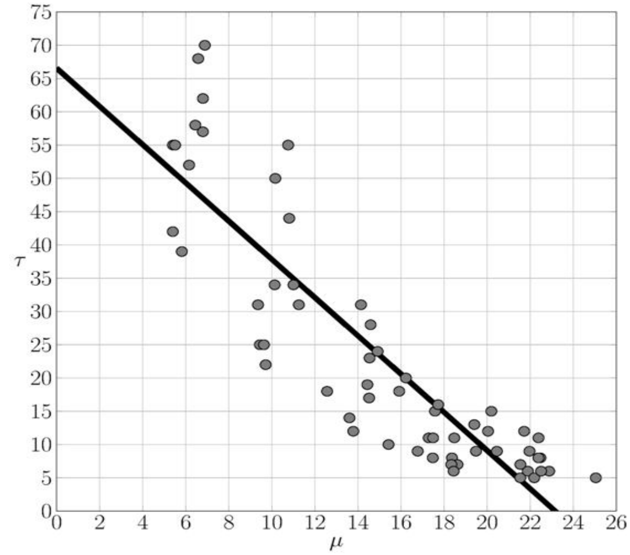

Figure 1. Dependence between the optimal threshold τ and the output of the noise detector for the images shown in Fig. 5.

IV. Comparison with Existing Techniques

For the evaluation of the effectiveness of the proposed filtering technique the test images were corrupted by a impulsive noise modeled in such a way, that the noisy pixel $x_i = \{x_{i1}, x_{i2}, x_{i3}\}$ is defined as:

$$x_i = \begin{cases} v_i, & \text{with probability } p \\ o_i, & \text{with probability } 1-p \end{cases} \tag{10}$$

where $v_i = \{v_{i1}, v_{i2}, v_{i3}\}$ and $v_{ik} \in \langle 0{,}255 \rangle,\ k = 1{,}2{,}3$. In this impulsive noise model, the affected pixels have corrupted all three channels, which take on random values from the interval *<0,255>*.

For the measurement of the restoration quality, the commonly used Root Mean Squared Error (RMSE) expressed through the Peak Signal to Noise Ratio (PSNR) was used, as the RMSE is a good measure of the efficiency of impulsive noise suppression and correlates well with other commonly used restoration quality measures [1].

The effectiveness of the proposed adaptive technique was compared with a set of switching filters intended for the suppression of impulsive noise in color images. The following filters were chosen for the comparison:

- Peer Group Filter (F_1), [18],
- Adaptive Center Weighted VMF (F_2), [19],
- Adaptive Center Weighted Directional-Distance Filter (F_3), [20],
- Rank-Ordered VMF (F_4), [21],
- Sigma Directional Distance Filter (F_5), [22].

Their parameters were set according to the recommendations provided in the appropriate references.

The four images depicted in Fig. 9 were contaminated by the impulsive noise with intensities ranging from 0.05 to 0.3. It is worth noticing, that these images were not included in the set of images used to establish the dependence expressed by Eq. (9). The results are summarized in Tab. 1.

As can be observed the proposed filtering method yields

results significantly superior to those obtained using the state-of-the-art denoising methods.

Figure 9. Test images used for the evaluation of the restoration results.

TABLE I. COMPARISON OF THE PSNR VALUES OBTAINED WHEN RESTORING THE COLOR TEST IMAGES CONTAMINATED WITH THE IMPULSIVE NOISE USING THE PROPOSED TECHNIQUE AND SOME COMPETITIVE FILTERS

Image	??	NEW	F_1	F_2	F_3	F_4	F_5
Goldhill	0.1	**37.14**	36.19	35.47	33.94	35.54	34.94
	0.2	**33.85**	32.66	31.07	30.53	32.26	29.57
	0.3	**31.33**	29.14	26.29	26.84	28.52	24.13
Lena	0.1	**39.81**	38.56	37.87	36.34	38.12	36.07
	0.2	**36.35**	34.54	31.93	31.69	33.98	29.46
	0.3	**33.35**	30.29	26.62	27.03	29.65	23.75
Parrots	0.1	**38.60**	37.32	36.73	36.78	36.29	36.70
	0.2	**35.55**	33.98	31.37	31.83	33.09	29.82
	0.3	**32.21**	29.43	26.03	26.73	28.59	23.81
Peppers	0.1	**41.62**	37.56	36.71	35.09	37.07	34.36
	0.2	**38.45**	33.42	30.79	30.27	32.75	27.59
	0.3	**34.31**	28.58	25.10	24.89	27.80	21.98

The results summarized in Tab. 1 are confirmed by the subjective analysis of the results depicted in Fig. 10, which shows the restoration quality achieved using the proposed filter as compared with other reference filters.

IV. CONCLUSIONS

In this paper a new switching filtering design has been proposed. The filter is based on the weighted cumulative distances between pixels, which are used for the detection of samples corrupted by impulsive noise process. The experiments performed on test images indicate a high efficiency of the proposed filtering design. Moreover, the new filter has a low computational complexity and simple structure, which makes it attractive for real-time applications.

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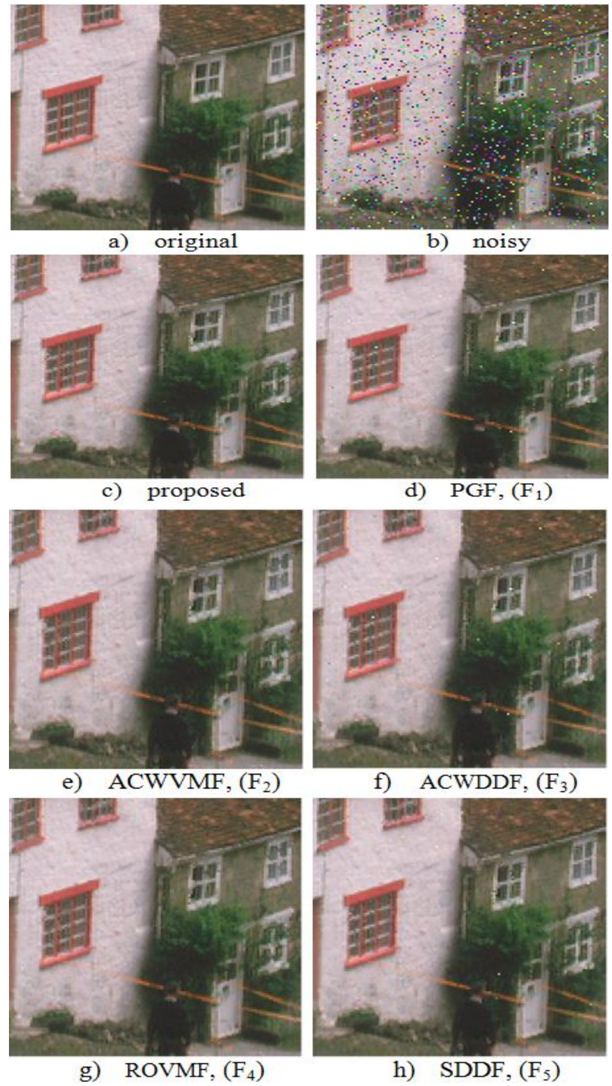

Figure 10. Comparison of the efficiency of the proposed technique with other methods using a part of the color test image GOLDHILL contaminated by impulsive noise with intensity $p = 0.1$

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